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Self-optimizing load balancing with backhaul-constrained radio access networks

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Abstract

Self-Organizing Network (SON) technology aims at autonomously deploying, optimizing and repairing the Radio Access Networks (RAN). SON algorithms typically use Key Performance Indicators (KPIs) from the RAN. It is shown that in certain cases, it is essential to take into account the impact of the backhaul state in the design of the SON algorithm. We revisit the Base Station (BS) load definition taking into account the backhaul state. We provide an analytical formula for the load along with a simple estimator for both elastic and guaranteed bit-rate (GBR) traffic. We incorporate the proposed load estimator in a self-optimized Load Balancing (LB) algorithm. Simulation results for a backhaul constrained heterogeneous network illustrate how the correct load definition can guarantee a proper operation of the SON algorithm.

Keywords

SON, Self-Organizing Networks, Load Balancing, Backhaul, backhaul-constrained load balancing, LTE

I. INTRODUCTION

The SON concept has been introduced by 3GPP [1] as a means to manage complexity, to reduce cost of operation, and to enhance performance and profitability of mobile networks. Self organizing networks aim at autonomously configuring newly deployed network nodes (self-configuration), at tuning parameters to improve Key Performance Indicators (KPIs) (self-optimization) and at diagnosing and repairing faulty network nodes (self-healing). Research on SON has mainly focused on the RAN with the assumption of infinite backhaul capacity. However, finite backhaul capacity may impact the RAN performance in general and the operation of SON functions in particular. This paper investigates self-optimizing LB algorithm in the case of finite backhaul capacity, and proposes solutions to guarantee correct operation of the algorithm.

Different SON algorithms for LB have been proposed in the literature (e.g. [2], [3], [4], [5]). The SON function monitors KPIs in the BSs and adjusts its parameters in order to steer those KPIs to desired values. In previous works, the KPIs are limited to the RAN, thus excluding finite backhaul capacity.

Network operators carefully dimension the backhaul to avoid capacity bottlenecks and to ensure end-to-end performance, while avoiding over dimensioning due to both equipment and deployment costs. In existing networks, and particularly for low power nodes such as small cells but not only, performance issues due to finite backhaul

capacity can be encountered in Asymmetric Digital Subscriber Line (ADSL) [6], or in wireless backhaul. In 5G networks, the high rate requirements for bandwidth intensive services [7] may cause saturation even in optical backhaul, unless very costly investment in the transport network are made.

The impact of the backhaul has been considered in non-3GPP networks e.g. in LB problems in Wireless Local Area Networks (WLANs) [8] where the authors propose load balancing algorithms but for a static scenario in which the number of users and their channel conditions are considered fixed. The backhaul limitations have been studied for LTE but only when it is used to exchange information between BSs e.g. in Coordinated Multi-Point (CoMP) [9]. The backhaul impact has also been studied in Radio Resource Management (RRM) mechanisms such as scheduling in [10] but with a static user association mechanism.

This paper analyses the impact of limited backhaul capacity on 3GPP LB SON taking into account the system dynamics. Numerical simulations show how a LB algorithm can fail when neglecting the limited backhaul. The contributions of the paper are the following:

- A global load definition for a BS taking into account the traffic demand and the capacity of both the backhaul and RAN.
- A simple and measurable estimator for the global load.
- Simulation results that show the limits of state-of-the-art load balancing algorithms in backhaul-constrained settings and the way these limits can be overcome using the global load indicator.

The rest of the paper is organized as follows. A classical definition of the load and a LB algorithm are recalled in Section II. The corrected load balancing algorithm is presented in Section III along with the modified load definition which takes into account the backhaul state. Section IV describes the numerical results which highlight the importance of using the correct load estimator to avoid significant performance deterioration. Section V concludes the paper.

II. LB FOR INFINITE-BACKHAUL

Consider the downlink of a mobile network such as the Long Term Evolution (LTE). We suppose that the backhaul has an infinite capacity or at least greater than the capacity of the BS. Two equivalent definitions can be used for the load of the BS: The first is the occupation rate of its resources. The second is the ratio between the traffic demand and the cell capacity which is valid for both elastic or GBR traffic.

In the case of a BS serving elastic traffic, users arrive randomly according to a Poisson process of intensity $\lambda(r)$ (in users/s/m²) at position r , download a file of random size σ with mean $\mathbb{E}(\sigma)$ (in Mbits) and leave the network when their download is complete. The load is written as [11]

$$\rho_e = \min \left(1, \int_A \frac{\lambda(r)\mathbb{E}(\sigma)}{R(r)} dr \right), \quad (1)$$

where A is the area of the considered cell, and $R(r)$ (in Mbps) is the peak data rate (i.e. when the user is alone in the cell) at position r averaged over fading.

If the BS also serves GBR traffic with fixed amount of resources allocated to the users, the priority is given to the GBR users. We consider that GBR traffic varies slowly with respect to elastic traffic (which is bursty) and is considered constant in (2). The load is redefined as

$$\rho = \min \left(1, \rho_{GBR} + \int_A \frac{\lambda(r)\mathbb{E}(\sigma)}{\bar{R}(r)} dr \right), \quad (2)$$

where $\bar{R}(r)$ is the peak data rate achievable at position r when using only the resources left after scheduling all GBR users, and ρ_{GBR} is the proportion of resources occupied by the GBR traffic at the radio access (in this case $\bar{R}(r) = (1 - \rho_{GBR})R(r)$). It is noted that this definition of the load does not depend on the scheduling algorithm which only impacts the user performance.

In practice, the load is estimated by the proportion of time-frequency resources that are occupied by the scheduler over a certain time period. We denote by K the total number of resource blocks available at a LTE BS, by K_t the number of resource blocks used at time slot t , and by T the total number of time slots over which the load is estimated. The load estimator is then given as

$$\hat{\rho} = \sum_{t=1}^T \frac{K_t}{K \cdot T}. \quad (3)$$

LB consists in updating certain RRM or system parameters in order to balance the load across BSs in the network.

We consider here a LB algorithm proposed in [3] that tunes the pilot powers of BSs in order to adjust the coverage of cells according to their loads. This algorithm has been developed for distributed and reactive operation, although it can be adapted for a centralized SON operation. The algorithm is presented in the form of a Stochastic Approximation (SA) update equation as follows:

$$P_s[t+1] = P_s[t] + \epsilon(\rho_0[t] - \rho_s[t]). \quad (4)$$

P_s is the pilot power of BS s , $\rho_s[t]$ - its load at time t , $\rho_0[t]$ - the load of the reference cell at time t , and ϵ - a constant step size. The reference BS can be chosen to be the most loaded cell in the considered area.

The authors in [3] have shown that as $\epsilon \rightarrow 0$ and $t \rightarrow +\infty$, P_s in (4) converges in probability to a set of pilot powers for which the loads of all the BSs are balanced on the average. Their proof relies on the elastic traffic scenario but the algorithm remains valid for GBR traffic as well. This LB algorithm has been extended in [12] to heterogeneous network scenario where each macro cell is surrounded by a number of small cells. The pilot powers are replaced with the Cell Individual Offset (CIO) of the small cells and the reference cell is chosen as the nearest macro cell. The CIO is used together with the Reference Signal Received Power (RSRP) to define the attachment rule for the User Equipment (UE)

$$s^* = \operatorname{argmax}_s \text{CIO}_s h_s^u P_s, \quad (5)$$

where s^* is the chosen serving cell, CIO_s - the CIO of cell s and h_s^u - the pathloss from BS s to UE u .

III. LB WITH LIMITED-BACKHAUL

In order to take into account the impact of backhaul capacity on LB algorithms, the BS load definition should be modified to include the backhaul occupancy. Indeed, when the backhaul is saturated while the BS capacity remains sufficient, KPIs such as outage probability or File Transfer Time (FTT) may drastically deteriorate. In this case, the buffer of the BS may be empty since the radio link traffic flows faster than the backhaul traffic feeding the buffer.

The load (1) for elastic traffic is rewritten taking into account the state of the backhaul as follows

$$\rho_{e,g} = \min \left(1, \int_A \frac{\lambda(r)\mathbb{E}(\sigma)}{\min(C_{BH}, R(r))} dr \right) \quad (6)$$

where C_{BH} is the capacity of the backhaul reserved for the RAN traffic. The subscript g stands for *global*, taking into account both BS and backhaul, as opposed to *local*.

The rationale behind Equation (6) is that the limited backhaul capacity may limit the peak data rate of a UE when alone in the cell. Hence Equation (1) should be modified by replacing $R(r)$ with $\min(C_{BH}, R(r))$. This modification is validated through simulation results in Section IV where we compare the adjusted load formula (in dashed lines in Figs. 3 and 4) with the actual load observed in the simulated system (plain lines in the Figures).

The load definition in (6) is modified if GBR traffic is also considered as follows

$$\rho_g = \min \left(1, \rho_{GBR,g} + \int_A \frac{\lambda(r)\mathbb{E}(\sigma)}{\min(\bar{C}_{BH}, \bar{R}(r))} dr \right). \quad (7)$$

\bar{C}_{BH} is the remaining backhaul capacity after backhaul resources have been allocated to GBR traffic. If we denote by D_{GBR} the total traffic demand of GBR users then $\bar{C}_{BH} = \max(0, C_{BH} - D_{GBR})$. $\rho_{GBR,g} = \max(\frac{D_{GBR}}{C_{BH}}, \rho_{GBR})$ is the global load of GBR traffic.

Load estimator

In practice, a simple load estimator can be derived, based on scheduler measurements. Consider first only elastic traffic and assume that all the resources are occupied even if only one user is present. Then the load can be estimated by the proportion of time that at least one user is present in the cell:

$$\rho_e = \sum_{t=1}^T \frac{\mathbf{1}_{\{x_e(t) > 0\}}}{T} \quad (8)$$

where $x_e(t)$ is the number of users at time slot t .

If we consider a mixed traffic scenario with priority given to GBR traffic, we get a general load estimator $\hat{\rho}_g$ that reads

$$\hat{\rho}_g = \frac{1}{T} \sum_{t=1}^T \mathbf{1}_{\{x_e(t) > 0\}} + \mathbf{1}_{\{x_e(t) = 0\}} \max(\gamma(t), \rho_{BH}(t)) \quad (9)$$

where $\gamma(t)$ is the proportion of resources used by the GBR traffic at time slot t in the RAN, and $\rho_{BH}(t)$ is the occupancy of the backhaul at time slot t .

The LB algorithm is then rewritten as follows

$$P_s[t+1] = P_s[t] + \epsilon(\hat{\rho}_{g,0}[t] - \hat{\rho}_{g,s}[t]) \quad (10)$$

where $\hat{\rho}_{g,s}$ and $\hat{\rho}_{g,0}$ are the global loads of cell s and the reference cell 0 respectively evaluated using Eq. (9). It is noted that the convergence proof of (10) is the same as in [3].

IV. NUMERICAL RESULTS

Consider a LTE network comprising a trisector macro BS surrounded by 6 interfering macro BSs. We select one sector and place in it 4 small cells (see Fig. 1). We consider only elastic traffic and evaluate the performance for the selected macro sector and the small cells inside its coverage area.

Two layers of traffic are superposed: the first one has a uniform arrival rate of λ users/s in the entire area (grey area in Fig. 1). The second one has a uniform arrival rate of λ_h users/s in the initial area covered by the small cells (with all CIOs set to 0dB), namely the small cells are deployed to serve the users in the hotspot areas.

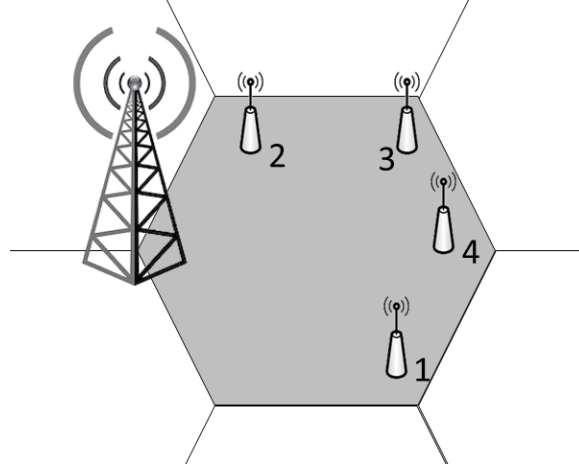


Fig. 1. Network Layout

To illustrate the impact of a bottleneck at the backhaul, we assume a low backhaul capacity of 10 Mbps. The propagation models for the macro BSs and the small cells (following [13, Page 61]) are presented in Table I which also summarizes the simulation parameters.

We simulate the system during 3 hours and compare side-by-side the performance obtained using Algorithms (4) and (10) denoted respectively as *Local SON* and *Global SON*. We present the results for the macro sector and for two of the small cells. We plot the analytical and the estimated loads (with $T = 60$ s) in dashed and plain lines respectively, using the different definitions (see Figs. 3 and 4). We also plot the CIOs (Fig. 2) set by the algorithms over time and the corresponding FTTs (Fig. 5).

The local SON balances the BSs' scheduler loads (see Fig. 3(a)) while it is unable to balance the real loads (see Fig. 3(b)). In particular, small cell 1 increases excessively its coverage area (see red curve in Fig. 2(a)) which causes its FTT to explode (red curve in Fig. 5(a)).

On the other hand, the Global SON balances the real loads (see Fig. 4(b)) by limiting the increase in small cells' CIOs (see Fig. 2(b)). As a consequence, the small cells' FTT remain low while the macro cell's FTT is decreased (see Fig. 5(b)).

It is noted that the size of small cell 2 is initially small because of its proximity to the macro cell. So the increase in its CIO does not increase too much its size, thus its performance remains good even with local SON as shown in Fig. 5(a).

TABLE I. NETWORK AND TRAFFIC PARAMETERS

Network parameters	
Number of cells	1 macro sector, 4 small cells
Number of interfering macros	6×3 sectors
Macro Cell layout	hexagonal trisector
Small Cell layout	omni
Intersite distance	500 m
Bandwidth	20MHz
Channel characteristics	
Thermal noise	-174 dBm/Hz
Macro Path loss (d in km)	$128 + 36.4 \log_{10}(d)$ dB
small cell Path loss (d in km)	$140.7 + 36.7 \log_{10}(d)$ dB
Traffic characteristics	
Traffic spatial distribution	uniform
(λ, λ_h)	(8,4) users/s
Service type	FTP
Average file size	4 Mbits

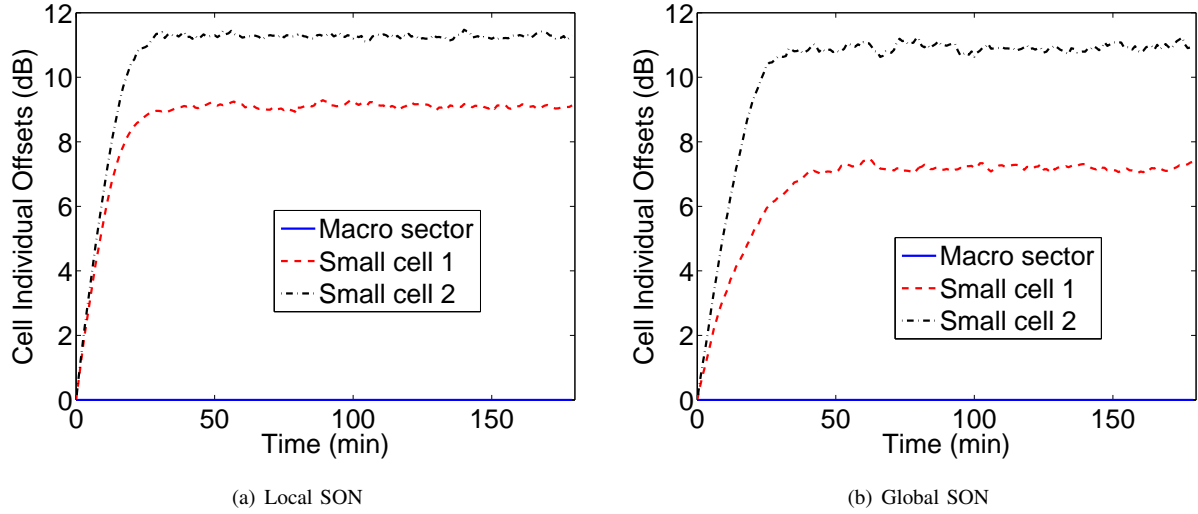


Fig. 2. Cell Individual Offsets

The overall user performance in terms of mean user throughput (MUT) and cell-edge throughput (CET) (see Fig. 6) also shows the superior performance of Global SON. At the beginning of the simulation period, the MUT is driven by the macro users which are more numerous. With the activation of the LB algorithms, the macro cell is progressively offloaded by the small cells, thus the MUT improves for both the local SON and the Global SON. When the real loads are balanced, the global SON stops increasing the small cells coverage thus ensuring that the MUT remains good. The local SON on the other hand continues to increase the small cells coverage in order to

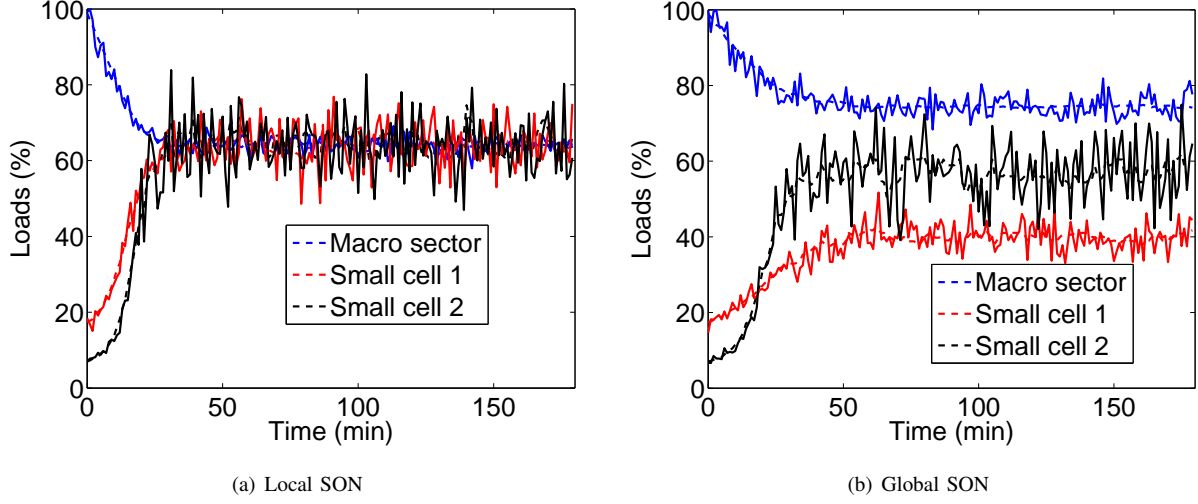


Fig. 3. Local loads using Eq. (2) (dashed lines) and Eq. (3) (plain lines)

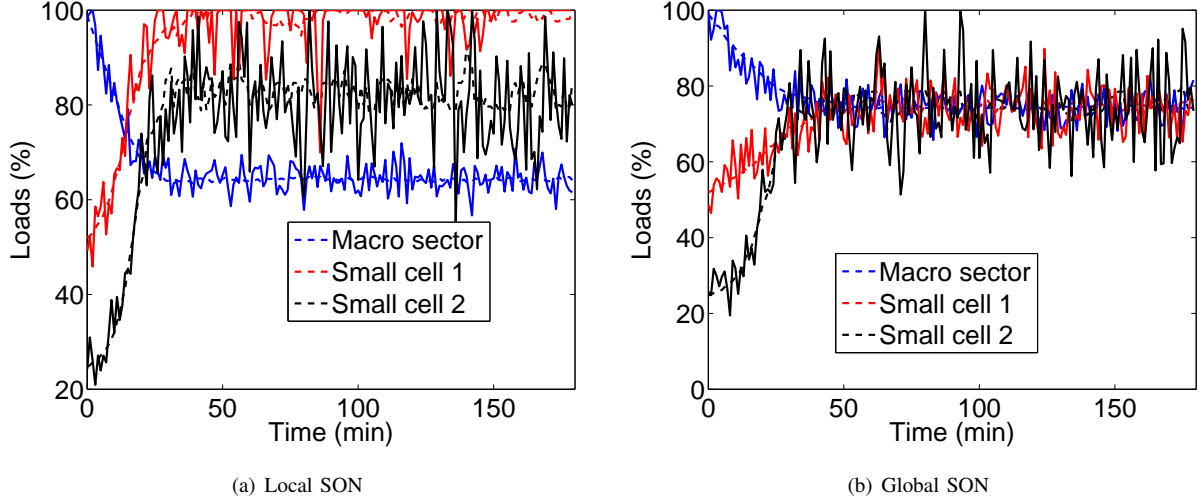


Fig. 4. Global loads using Eq. (6) (dashed lines) and Eq. (8) (plain lines)

balance the scheduler loads. This leads to the backhaul saturation of certain small cells which see their performance degrade drastically and consequently, to the degradation of the overall MUT. The same behavior is observed for the CET but this time the performance degradation for the local SON occurs earlier because cell edge users are more impacted by an overload in the system. It is noted that the proposed algorithm (10) has been proven robust to non-stationary traffic demands through extensive simulations.

V. CONCLUSION

This paper has presented the impact of finite backhaul capacity on the performance of LB in the RAN. It has been shown that by properly defining load indicators that take into account both the BS and the backhaul loads, one can guarantee the proper operation of the LB algorithm. If one neglects the finite backhaul capacity, the offloading BS

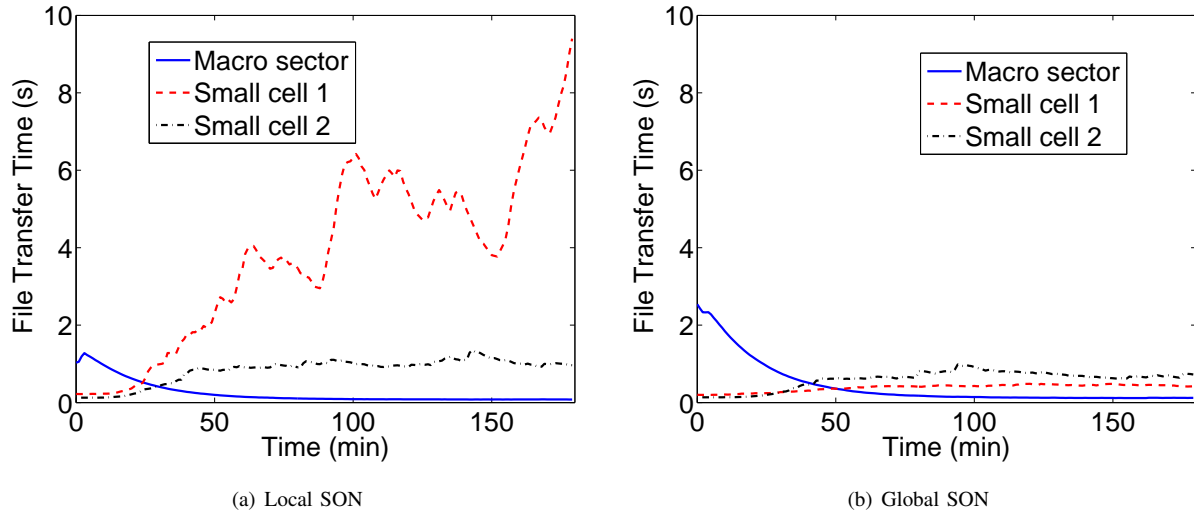


Fig. 5. File Transfer Time

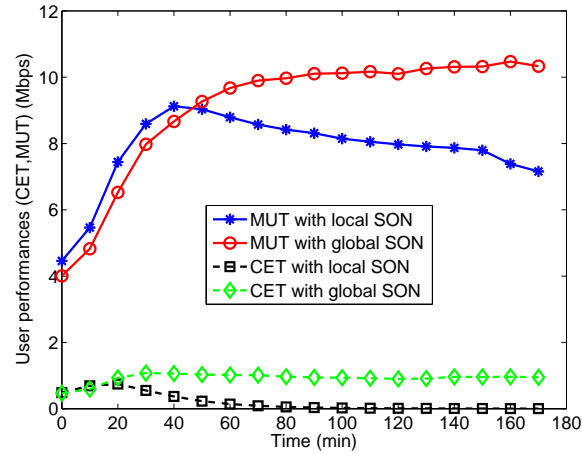


Fig. 6. Time evolution of MUT and CET for the cluster of the macro BS and the 4 small cells

can saturate. A load estimator based on measurements has been proposed that takes into account the backhaul state. Simulation results of load balancing in a heterogeneous network with small cells and limited backhaul capacity have illustrated the importance of using the correct load definition to avoid possible performance deterioration. The impact of finite backhaul capacity on other SON algorithms such as Mobility Robustness Optimization (MRO) or Inter-Cell Interference Coordination (ICIC) would be a natural extension of this work.

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